

# Non-Monotonic Reasoning and Story Comprehension

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## Abstract

This paper develops a Reasoning about Actions and Change framework integrated with Default Reasoning, suitable as a Knowledge Representation and Reasoning framework for Story Comprehension. The proposed framework, which is guided strongly by existing knowhow from the Psychology of Reading and Comprehension, is based on the theory of argumentation from AI. It uses argumentation to capture appropriate solutions to the frame, ramification and qualification problems and generalizations of these problems required for text comprehension. In this first part of the study the work concentrates on the central problem of integration (or elaboration) of the explicit information from the narrative in the text with the implicit (in the reader's mind) common sense world knowledge pertaining to the topic(s) of the story given in the text. We also report on our empirical efforts to gather background common sense world knowledge used by humans when reading a story and to evaluate, through a prototype system, the ability of our approach to capture both the majority and the variability of understanding of a story by the human readers in the experiments.

## Introduction

Text comprehension has long been identified as a key test for Artificial Intelligence (AI). Aside from its central position in many forms of the Turing Test, it is clear that human computer interaction could benefit enormously from this and other forms of natural language processing. The rise of computing over the Internet, where so much data is in the form of textual information, has given even greater importance to this topic. This paper reports on a research program aiming to learn from the (extensive) study of text comprehension in Psychology in order to draw guidelines for developing frameworks for automating narrative text comprehension and in particular, *story comprehension* (SC).

Our research program brings together knowhow from Psychology and AI, in particular, our understanding of Reasoning about Actions and Change and Argumentation in AI, to provide a formal framework of representation and a computational framework for SC, that can be empirically evaluated and iteratively developed given the results of the evaluation. This empirical evaluation, which forms an important part of the program, is based on the following methodology: (i) set up a set of stories and a set of questions to test different aspects of story comprehension; (ii) harness the

world knowledge on which human readers base their comprehension; (iii) use this world knowledge in our framework and automated system and compare its comprehension behaviour with that of the source of the world knowledge.

In this paper we will concentrate on the development of an appropriate Reasoning about Actions and Change and Default Reasoning framework for representing narratives extracted from stories together with the background *world knowledge* needed for the underlying central process for story comprehension of *synthesizing and elaborating* the explicit text information with new inferences through the implicit world knowledge of the reader. In order to place this specific consideration in the overall process of story comprehension we present here a brief summary of the problem of story comprehension from the psychological point of view.

## A Psychological Account of Story Comprehension

Comprehending text entails the construction of a mental representation of the information contained in the text. However, no text specifies clearly and completely all the implications of text ideas or the relations between them. Therefore, comprehension depends on the ability to mentally represent the text-given information and to generate **bridging and elaborative inferences** that connect and elaborate text ideas resulting in a mental or **comprehension model** of the story. Inference generation is necessary in order to comprehend any text as a whole, i.e., as a single network of interconnected propositions instead of as a series of isolated sentences, and to appreciate the suspense and surprise that characterize narrative texts or stories, in particular (Brewer and Lichtenstein 1982; McNamara and Magliano 2009).

Although inference generation is based on the activation of background **world knowledge**, the process is constrained by text information. Concepts encountered in the text activate related conceptual knowledge in the readers' long-term memory (Kintsch 1988). In the case of stories, knowledge about mental states, emotions, and motivations is also relevant as the events depicted tend to revolve around them. Nevertheless, at any given point in the process, only a small subset of all the possible knowledge-based inferences remain activated and become part of the mental representation: those that connect and elaborate text information in a way that contributes to the **coher-**

**ence** of the mental model (McNamara and Magliano 2009; Rapp and den Broek 2005). Inference generation is a task-oriented process that follows the principle of **cognitive economy** enforced by a limited-resource cognitive system.

However, the results of this coherence-driven selection mechanism can easily exceed the limited working memory capacity of the human cognitive system. Therefore, coherence on a more global level is achieved through **higher-level integration** processes that operate to create macro-propositions that generalize or subsume a number of text-encountered concepts and the inferences that connected them. In the process, previously selected information that maintains few connections to other information is dropped from the mental model. This results in a more consolidated network of propositions that serves as the new anchor for processing subsequent text information (Kintsch 1998).

Comprehension also requires an iterative general **revision mechanism** of the mental model that readers construct. The feelings of suspense and surprise that stories aim to create are achieved through discontinuities or changes (in settings, motivations, actions, or consequences) that are not predictable or are wrongly predictable solely on the basis of the mental model created so far. Knowledge about the structure and the function of stories leads readers to expect discontinuities and to use them as triggers to revise their mental model (Zwaan 1994). Therefore, a change in time or setting in the text may serve as a clue for revising parts of the mental model while other parts remain and integrated with subsequent text information.

The interaction of bottom-up and top-down processes for the purposes of coherence carries the possibility of **different** but equally legitimate or **successful comprehension** outcomes. Qualitative and quantitative differences in conceptual and mental state knowledge can give rise to differences between the mental models constructed by different readers. Nevertheless, comprehension is successful if these are primarily differences in elaboration but not in the level of coherence of the final mental model.

In this paper we will focus on the underlying lower-level task of constructing the possibly additional elements of the comprehension model and the process of revising these elements as the story unfolds with only a limited concern on the global requirements of coherence and cognitive economy. Our working hypothesis is that these higher level features of comprehension can be tackled on top of the underlying framework that we are developing in this paper, either at the level of the representational structures and language or with additional computational processes on top of the underlying computational framework defined in this paper. We are also assuming as solved the orthogonal issue of correctly parsing the natural language of the text into some information-equivalent structured (e.g., logical) form that gives us the explicit narrative of the story. This is not to say that this issue is not an important element of narrative text comprehension. Indeed, it may need to be tackled in conjunction with the problems on which we are focusing (since, for example, the problem of de-referencing pronoun and article anaphora could depend on background world knowledge and hence possibly on the higher-level whole comprehension of the

text (Levesque, Davis, and Morgenstern 2012).

In the next two sections we will develop an appropriate representation framework using preference based argumentation that enables us to address well all the three major problems of *frame, ramification and qualification* and provide an associated revision process. The implementation of a system discussed after this shows how psychologically-inspired story comprehension can proceed as a sequence of elaboration and revision. The paper then presents, using the empirical methodology suggested by research in psychology, our initial efforts to evaluate how closely the inferences drawn by our framework and system match those given by humans engaged in a story comprehension task.

The following story will be used as a running example.

**Story:** *It was the night of Christmas Eve. After feeding the animals and cleaning the barn, Papa Joe took his shotgun from above the fireplace and sat out on the porch cleaning it. He had had this shotgun since he was young, and it had never failed him, always making a loud noise when it fired.*

*Papa Joe woke up early at dawn, picked up his shotgun and went off to forest. He walked for hours, until the sight of two turkeys in the distance made him stop suddenly. A bird on a tree nearby was cheerfully chirping away, building its nest. He aimed at the first turkey, and pulled the trigger.*

*After a moment's thought, he opened his shotgun and saw there were no bullets in the shotgun's chamber. He loaded his shotgun, aimed at the turkey and pulled the trigger again. Undisturbed, the bird nearby continued to chirp and build its nest. Papa Joe was very confused. Would this be the first time that his shotgun had let him down?*

The story above along with other stories and material used for the evaluation of our approach can be found at <http://cognition.ouc.ac.cy/narrative/>.

## KRR for Story Comprehension

We will use methods and results from Argumentation Theory in AI (e.g., (Dung 1995; Modgil and Prakken 2012)) and its links to the area of Reasoning about Action and Change (RAC) with Default Reasoning on the static properties of domains (see (van Harmelen, Lifschitz, and Porter 2008) for an overview) to develop a Knowledge Representation and Reasoning (KRR) framework suitable for Story Comprehension (SC). Our central premise is that SC can be formalized in terms of argumentation accounting for the qualification and the revision of the inferences drawn as we read a story.

The psychological research and understanding of SC will guide us in the way we exploit the know how from AI. The close link between human common sense reasoning, such as that for SC, and argumentation has been recently re-enforced by new psychological evidence (Mercier and Sperber 2011) suggesting that human reasoning is in its general form inherently argumentative. In our proposed approach of KRR for SC the reasoning to construct a comprehension model and its qualification at all levels as the story unfolds will be captured through a uniform acceptability requirement on the arguments that support the conclusions in the model.

The significance of this form of representation for SC is that it makes easy the elaboration of new inferences from the

explicit information in the narrative, that, as we discussed in the introduction, is crucially necessary for the successful comprehension of stories. On the other hand, this easy form of elaboration and the extreme form of qualification that it needs can be mitigated by the requirement, again given from the psychological perspective, that elaborative inferences need to be *grounded* on the narrative and *sceptical* in nature. In other words, the psychological perspective of SC, that also suggests that story comprehension is a process of “*fast thinking*”, leads us to depart from a standard logical view of drawing conclusions based on the truth in all (preferred) models. Instead, the emphasis is turned on building one *grounded and well-founded* model from a collection of solid or sceptical properties that are grounded on the text and follow as unqualified conclusions.

We use a typical RAC language of Fluents, Actions, Times, with an extra sort of **Actors**. An actor-action pair is an *event*, and a fluent/event or its negation is a *literal*. For this paper it suffices to represent times as natural numbers<sup>1</sup> and to assume that time-points are dense between story elements to allow for the realization of indirect effects. Arguments will be build from premises in the knowledge connected to any given story. We will have three types of such knowledge units as premises or basic units of arguments.

**Definition 1.** Let  $L$  be a fluent literal,  $X$  a fluent/event literal and  $S$  a set of fluent/event literals. A **unit argument or premise** has one of following forms:

- a **unit property argument**  $\text{pro}(X, S)$  or  $\text{prec}(X, S)$ ;
- a **unit causal argument**  $\text{cau}(X, S)$ ;
- a **unit persistence argument**  $\text{per}(L, \{L\})$  (which we sometimes write as  $\text{per}(L, \cdot)$ ).

These three forms are called **types** of unit arguments. A unit argument of any type is denoted by  $\text{arg}_i(H_i, B_i)$ . The two forms of unit property arguments differ in that  $\text{pro}(X, S)$  relates properties to each other at the same time-point, whereas  $\text{prec}(X, S)$  aims to capture preconditions that hold at the time-point of an event, under which the event is blocked from bringing about its effects at the subsequent time-point.

With abuse of terminology we will sometimes call these units of arguments, simply as arguments.

The knowledge required for the comprehension of a story comprises of two parts: the explicit knowledge of the narrative extracted from the text of the story and the implicit background knowledge that the reader uses along with the narrative for elaborative inferences about the story.

**Definition 2.** A **world knowledge theory**  $\mathcal{W}$  is a set of unit property and causal arguments together with a (partial) irreflexive priority relation on them. A **narrative**  $\mathcal{N}$  is: a set of observations  $\text{OBS}(X, T)$  for a fluent/event literal  $X$ , and a time-point  $T$ ; together with a (possibly empty) set of (story specific) property or causal unit arguments.

The priority relation in  $\mathcal{W}$  would typically reflect the priority of specificity for properties, expressed by unit property arguments  $\text{pro}(X, S)$ , or the priority of precondition properties, expressed by unit property arguments  $\text{prec}(X, S)$ ,

over causal effects, expressed by unit causal arguments. This priority amongst these basic units of knowledge gives a form of non-monotonic reasoning (NMR) for deriving new properties that hold in the story.

To formalize this NMR we use a form of preference-based argumentation uniformly to capture the static (default) inference of properties at a single time point as well as inferences between different type points, by extending the domain specific priority relation to address the frame problem.

**Definition 3.** A **story representation**  $\mathcal{SR} = \langle \mathcal{W}, \mathcal{N}, \succ \rangle$  comprises a world knowledge theory  $\mathcal{W}$ , a narrative  $\mathcal{N}$ , and a (partial) irreflexive priority relation  $\succ$  extending the one in  $\mathcal{W}$  so that: (i)  $\text{cau}(H, B_1) \succ \text{per}(\neg H, B_2)$ ; (ii)  $\text{per}(H, B_1) \succ \text{pro}(\neg H, B_2)$ . The extended relation  $\succ$  may also prioritize between arguments in  $\mathcal{N}$  and those in  $\mathcal{W}$  (typically the former over the latter).

The first priority condition, namely that causal arguments have priority over persistence arguments, encompasses a solution to the **frame problem**. When we need to reason with defeasible property information, such as default rules about the normal state of the world in which a story takes place, we are also faced with a **generalized frame problem**, where “a state of the world persists irrespective of the existence of general state laws”. Hence, if we are told that the world is in fact in some exceptional state that violates a general (default) property this will continue to be the case in the future, until we learn of (or derive) some causal information that returns the world into its normal state. The solution to this generalized frame problem is captured succinctly by the second general condition on the priority relation of a story representation and its combination with the first condition.

A representation  $\mathcal{SR}$  of our example story (focusing on its ending) may include the following unit arguments in  $\mathcal{W}$  and  $\mathcal{N}$  (where  $pj$  is short for “Papa Joe”):

$c1 : \text{cau}(\text{fired\_at}(pj, X), \{\text{aim}(pj, X), \text{pull\_trigger}(pj)\})$   
 $c2 : \text{cau}(\neg \text{alive}(X), \{\text{fired\_at}(pj, X), \text{alive}(X)\})$   
 $c3 : \text{cau}(\text{noise}, \{\text{fired\_at}(pj, X)\})$   
 $c4 : \text{cau}(\neg \text{chirp}(\text{bird}), \{\text{noise}, \text{nearby}(\text{bird})\})$   
 $c5 : \text{cau}(\text{gun\_loaded}, \{\text{load\_gun}\})$   
 $p1 : \text{prec}(\neg \text{fired\_at}(pj, X), \{\neg \text{gun\_loaded}\})$   
 $p2 : \text{pro}(\neg \text{fired\_at}(pj, X), \{\neg \text{noise}\})$  (story specific)

with  $p1 \succ c1, p2 \succ c1$ ; and the following in  $\mathcal{N}$ :

$\text{OBS}(\text{alive}(\text{turkey}), 1), \quad \text{OBS}(\text{aim}(pj, \text{turkey}), 1),$   
 $\text{OBS}(\text{pull\_trigger}(pj), 1), \quad \text{OBS}(\neg \text{gun\_loaded}, 4),$   
 $\text{OBS}(\text{load\_gun}, 5), \quad \text{OBS}(\text{pull\_trigger}(pj), 6),$   
 $\text{OBS}(\text{chirp}(\text{bird}), 10), \quad \text{OBS}(\text{nearby}(\text{bird}), 10),$

with the exact time-point choices being inconsequential.

As we can see in this example the representation of common sense world knowledge has the form of simple associations between concepts in the language. This stems from a key observation in psychology that typically all world knowledge and irrespective of type is inherently default. It is not in the form of an elaborate formal theory of detailed definitions of concepts, but rather is better regarded as a collection of relatively loose semantic associations between concepts, reflecting typical rather than absolute information.

<sup>1</sup>In general, abstract time points called *scenes* are useful.

Thus knowledge need not be fully qualified at the representation level, since it can be qualified via the reasoning process by the relative strength of other (conflicting) associations in the knowledge. In particular, as we will see below, **endogenous qualification** will be tackled by the priority relation in the theory and exogenous qualification by this priority coupled with the requirement that explicit narrative information forms, in effect, non-defeasible arguments.

### Argumentation Semantics for Stories

To give the semantics of any given story representation  $\mathcal{SR}$  we will formulate a corresponding preference based argumentation framework of the form  $\langle \text{Arguments}, \text{Disputes}, \text{Defences} \rangle$ . Arguments will be based on sets of timed unit arguments. Since we are required to reason about properties over time, it is necessary that arguments populate some connected subset of the time line.

**Definition 4.** Let  $\mathcal{SR} = \langle \mathcal{W}, \mathcal{N}, \succ \rangle$  be a story representation. A **(unit) argument tuple** has the form  $\langle \arg(H, B), T^h, d; (X, T) \rangle$ , where,  $\arg(H, B)$ , is a unit argument in  $\mathcal{SR}$ ,  $X$  is a fluent/event literal,  $d \in \{F, B\}$  is an **inference type** of either forwards derivation or backwards derivation by contradiction, and  $T^h, T$  are time points.  $T^h$  refers to the time-point at which the head of the unit argument applies, while  $X$  and  $T$  refer to the conclusion drawn using the unit argument in the tuple. An **interpretation**  $\Delta$  of  $\mathcal{SR}$  is then defined as a set of argument tuples. We say  $\Delta$  **supports** a fluent/event literal,  $X$ , **at**  $T$ , if either  $\langle \arg(H, B), T^h, d; (X, T) \rangle \in \Delta$  or  $\text{OBS}(X, T) \in \mathcal{N}$ . The notion of support is extended to hold on sets of timed literals.

The inference process of how an argument tuple supports a timed literal, and thus is allowed to belong to an interpretation, is made precise by the following definition.

**Definition 5.** Let  $\Delta$  be an interpretation and  $\langle \arg(H, B), T^h, d; (X, T) \rangle$  in  $\Delta$  with  $d = F$ . Then  $\arg(H, B)$  **applied at  $T^h$  forward derives  $X$  at  $T$  under  $\Delta$**  iff  $X = H$ ,  $T = T^h$  and  $\Delta$  supports  $B$  at  $T'$ . The set  $\{\langle Y, T' \rangle \mid Y \in B\}$  is called the **activation condition** for the derivation;  $T' = T^h$  if  $\arg(H, B)$  is of the form  $\text{pro}(H, B)$ .  $T' = T^h - 1$  for the other argument types. When  $d = B$ ,  $\arg(H, B)$  **applied at  $T^h$  backward derives  $X$  at  $T$  under  $\Delta$**  iff  $\neg X \in B$  and  $\Delta$  supports  $\{\neg H\}$  at  $T^h$  and  $B \setminus \{\neg X\}$  at  $T$ . The set  $\{\langle \neg H, T^h \rangle\} \cup \{\langle Y, T' \rangle \mid Y \in B \setminus \{\neg X\}\}$  is the **activation condition**;  $T = T^h$  if  $\arg(H, B)$  is of the form  $\text{pro}(H, B)$ .  $T = T^h - 1$  for the other argument types.

The framework thus includes **reasoning by contradiction** with the defeasible world knowledge. Although the psychological debate on the question to what extent humans reason by contradiction, e.g., by contraposition, (see, e.g., (Johnson-Laird and Yang 2008; Rips 1994)) is still ongoing it is natural for a formal argumentation framework to capture this mode of indirect reasoning (see, e.g., (Kakas, Toni, and Mancarella 2013; Kakas and Mancarella 2013)). One of the main consequences of this is that it gives a form of **backwards persistence**, e.g., from an observation to support (but not nec-

essarily conclude) that the observed property holds also at previous time points. An argument tuple of the form  $\langle \text{per}(L, \cdot), T + 1, B; (\neg L, T) \rangle$  captures the backwards persistence of  $\neg L$  from time  $T + 1$  to  $T$  using by contraposition the unit argument of persistence of  $L$  from  $T$  to  $T + 1$ . We also note that the separation of the inference type (e.g., forwards and backwards) is known to be significant in preference based argumentation (Modgil and Prakken 2012). This will be exploited when we consider the attacking between arguments: their disputes and defences.

To reflect the suggestion by psychology that inferences drawn by readers are strongly tied to the story we require that the activation conditions of argument tuples must be eventually traced on the explicit information in the narrative of the story representation.

**Definition 6.** An interpretation  $\Delta$  is **grounded** on  $\mathcal{SR}$  iff there is a total ordering of  $\Delta$  such that the activation condition of any tuple  $\alpha \in \Delta$  is supported by the set of tuples that precede  $\alpha$  in the ordering or by the narrative in  $\mathcal{SR}$ .

Hence in a grounded interpretation there can be no cycles in the tuples that support their activation conditions and so these will always end with tuples whose activation conditions will be supported directly by the observations in the narrative of the story.

We can now define the argumentation framework corresponding to any given story representation. The central task is to capture through the argumentation semantics the non-monotonic reasoning of linking the narrative to the defeasible information in the world knowledge. In particular, the argumentation will need to capture the **qualification** problem, encompassed in this synthesis of the narrative with the world knowledge, both at the level of static reasoning at one time point with default property arguments and at the level of temporal projection from one time point to another.

**Definition 7.** Let  $\mathcal{SR}$  be a story representation. Then the **corresponding argumentation framework**,  $\langle \text{ARG}^{\mathcal{SR}}, \text{DIS}^{\mathcal{SR}}, \text{DEF}^{\mathcal{SR}} \rangle$  is defined as follows:

- An argument,  $A$ , in  $\text{ARG}^{\mathcal{SR}}$  is any grounded interpretation of  $\mathcal{SR}$ .
- Given an argument  $A$  then  $A$  is **in conflict** with  $\mathcal{SR}$  iff there exists a tuple  $\alpha = \langle \arg(H, B), T^h, d; (X, T) \rangle$  in  $A$  such that  $\text{OBS}(\neg X, T) \in \mathcal{N}$  of  $\mathcal{SR}$ .
- Given two arguments  $A_1, A_2$  then these are **in (direct) conflict** with each other iff there exists a tuple  $\alpha_2 = \langle \arg_2(H_2, B_2), T_2^h, d_2; (X_2, T_2) \rangle$  in  $A_2$  and a tuple  $\alpha_1 = \langle \arg_1(H_1, B_1), T_1^h, d_1; (X_1, T_1) \rangle$  in  $A_1$  such that  $X_1 = \neg X_2$ ,  $T_1 = T_2$ . Given two arguments  $A_1, A_2$  then these are **in indirect conflict** with each other iff there exists a tuple  $\alpha_2 = \langle \arg_2(H_2, B_2), T_2^h, d_2; (X_2, T_2) \rangle$  in  $A_2$  and a tuple  $\alpha_1 = \langle \arg_1(H_1, B_1), T_1^h, d_1; (X_1, T_1) \rangle$  in  $A_1$  such that  $(d_1 = B \text{ or } d_2 = B)$  and  $H_1 = \neg H_2$ ,  $T_1^h = T_2^h$ .
- Given two arguments  $A_1, A_2$  then  $A_2$  **disputes**  $A_1$  and hence  $(A_2, A_1) \in \text{DIS}^{\mathcal{SR}}$  iff  $A_2$  is in direct or indirect conflict with  $A_1$ , and in the case of indirect conflict  $d_1 = B$  holds in the definition of indirect conflict above.
- Argument  $A_1$  **undercuts**  $A_2$  iff

- $A_1, A_2$  are in direct or indirect conflict via  $\alpha_1$  and  $\alpha_2$ ,
- when in direct conflict, there exists a tuple  $\alpha'_1 = \langle \arg'_1(H'_1, B'_1), T'_1, d'_1; (X'_1, T'_1) \rangle$  in  $A_1$  and a tuple  $\alpha'_2 = \langle \arg'_2(H'_2, B'_2), T'_2, d'_2; (X'_2, T'_2) \rangle$  in  $A_2$  such that  $\arg'_1(H'_1, B'_1) \succ \arg'_2(H'_2, B'_2)$  and  $T'_1 = T'_2$  or  $T'_1 = T'_2$ .
- when in indirect conflict, then  $\arg_1(H_1, B_1) \succ \arg_2(H_2, B_2)$  where  $\arg_1(H_1, B_1)$  and  $\arg_2(H_2, B_2)$  are the unit arguments in  $\alpha_1$  and  $\alpha_2$  respectively.
- Argument  $A_1$  **defends against**  $A_2$  and hence  $(A_1, A_2) \in DEF^{SR}$ , iff there exists a subset  $A'_2 \subseteq A_2$  which is in minimal conflict with  $A_1$  (i.e., no proper subset of  $A'_2$  is in conflict with  $A_1$ ) and  $A_1$  undercuts  $A'_2$ .

Several clarifying comments are in order. Arguments that are in dispute are arguments that support some contrary conclusion at the same time point and hence form counter-arguments for each other. The use of contrapositive reasoning for backwards inference also means that it is possible to have arguments that support conclusions that are not contrary to each other but whose unit arguments have conflicting conclusions. For example, in our running example we can use the causal unit argument,  $c1$ , to forward derive  $fired\_at(pj, X)$  and the property argument  $p1$  to backwards derive  $gun\_loaded$  from  $\neg fired\_at(pj, X)$  and despite the fact that the derived facts are not in conflict the unit arguments used concern conflicting conclusions. Hence such arguments are also considered to be in conflict but instead of a direct conflict we say we have an indirect conflict. Not all such indirect conflicts are important. A dispute that results from an indirect conflict of a unit argument used backwards on a unit argument that is used forwards does not have any effect. Such cases are excluded from giving rise to disputes.

This complication in the definitions of conflicts and disputes results from the *defeasible nature* of the world knowledge and the fact we are allowing reasoning by contradiction on such defeasible information. These complications in fact stem from the fact that we are only approximating the proof by contradiction reasoning, capturing this indirectly through contraposition. The study of this is beyond the scope of this paper and the reader is referred to the newly formulated Argumentation Logic (Kakas, Toni, and Mancarella 2013).

Undercuts between arguments require that the undercutting argument does so through a stronger unit or premise argument than some unit argument in the argument that is undercut. The defence relation is build out of undercuts by applying an undercut on minimally conflicting subsets of the argument which we are defending against. Hence these two relations between arguments are asymmetric. Note also that the stronger premise from the undercutting argument does not necessarily need to come from the subset of the unit arguments that supports the conflicting conclusion. Instead, it can come from any part of the undercutting argument to undercut at any point of the chain supporting the activation of the conflicting conclusion. This, as we shall illustrate below, is linked to how the framework addresses the **ramification problem** of reasoning with actions and change.

The semantics of a story representation is defined using the corresponding argumentation framework as follows.

**Definition 8.** Let  $SR$  be a story representation and  $\langle ARG^{SR}, DIS^{SR}, DEF^{SR} \rangle$  its corresponding argumentation framework. An argument  $\Delta$  is **acceptable** in  $SR$  iff

- $\Delta$  is not in conflict with  $SR$  nor in direct conflict with  $\Delta$ .
- No argument  $A$  undercuts  $\Delta$ .
- For any argument  $A$  that minimally disputes  $\Delta$ ,  $\Delta$  defends against  $A$ .

Acceptable arguments are called **comprehension models** of  $SR$ . Given a comprehension model  $\Delta$ , a timed fluent literal  $(X, T)$  is **entailed by**  $SR$  iff this is supported by  $\Delta$ .

The above definition of comprehension model and story entailment is of a sceptical form where, apart from the fact that all conclusions must be ground on the narrative, they must also not be non-deterministic in the sense that there can not exist another comprehension model where the negative conclusion is entailed. Separating disputes and undercuts and identifying defences with undercuts facilitates this sceptical form of entailment. Undercuts (see, e.g., (Modgil and Prakken 2012) for some recent discussion) are strong counter-claims whose existence means that the attacked set is inappropriate for sceptical conclusions whereas disputes are weak counter-claims that could be defended or invalidated by extending the argument to undercut them back. Also the explicit condition that an acceptable argument should not be undercut even if it can undercut back means that this definition does not allow non-deterministic choices for arguments that can defend themselves.

To illustrate the formal framework, how arguments are constructed and how a comprehension of a story is formed through acceptable arguments let us consider our example story starting from the end of the second paragraph, corresponding to time-points 1-3 in the example narrative. Note that the empty  $\Delta$  supports  $aim(pj, turkey)$  and  $pull\_trigger(pj)$  at 1. Hence,  $c1$  on 2 forward activates  $fired\_at(pj, turkey)$  at 2 under the empty argument,  $\Delta$ . We can thus populate  $\Delta$  with  $\langle c1, 2, F; (fired\_at(pj, turkey), 2) \rangle$ . Similarly, we can include  $\langle per(alive(turkey), \cdot), 2, F; (alive(turkey), 2) \rangle$  in the new  $\Delta$ . Under this latter  $\Delta$ ,  $c2$  on 3 forward activates  $\neg alive(turkey)$  at 3, allowing us to further extend  $\Delta$  with  $\langle c2, 3, F; (\neg alive(turkey), 3) \rangle$ . The resulting  $\Delta$  is a grounded interpretation that supports  $\neg alive(turkey)$  at 3. It is based on this inference, that we expect readers to respond that the first turkey is dead, when asked about its status at this point, since no other argument grounded on the narrative (thus far) can support a qualification argument to this inference. Note also that we can include in  $\Delta$  the tuple  $\langle p1, 2, B; (gun\_loaded, 1) \rangle$  to support, using backwards (contrapositive) reasoning with  $p1$ , the conclusion that the gun was loaded when it was fired at time 1.

Reading the first sentence of the third paragraph, we learn that  $OBS(\neg gun\_loaded, 4)$ . We now expect that this new piece of evidence will lead readers to revise their inferences as now we have an argument to support the conclusion  $\neg fired\_at(pj, turkey)$  based on the stronger (qualifying)

unit argument of  $p1$ . For this we need to support the activation condition of  $p1$  at time 1, i.e., to support  $\neg \text{gun\_loaded}$  at 1. To do this we can use the argument tuples:

$\langle \text{per}(\text{gun\_loaded}, \cdot), 4, B; (\neg \text{gun\_loaded}, 3) \rangle$   
 $\langle \text{per}(\text{gun\_loaded}, \cdot), 3, B; (\neg \text{gun\_loaded}, 2) \rangle$   
 $\langle \text{per}(\text{gun\_loaded}, \cdot), 2, B; (\neg \text{gun\_loaded}, 1) \rangle$

which support the conclusion that the gun was also unloaded before it was observed to be so. This uses  $\text{per}(\text{gun\_loaded}, \cdot)$  contrapositively to backward activate the unit argument of persistence, e.g., had the gun been loaded at 3, it would have been so at 4 which would contradict the story. Note that this backwards inference of  $\neg \text{gun\_loaded}$  would be qualified by a causal argument for  $\neg \text{gun\_loaded}$  at any time earlier than 4, e.g., if the world knowledge contained the unit argument

$c : \text{cau}(\neg \text{gun\_loaded}, \{\text{pull\_trigger}(pj)\})$

This then supports an indirect conflict at time 2 with the forwards persistence of  $\text{gun\_loaded}$  from 1 to 2 and due to the stronger nature of unit causal over persistence arguments the backwards inference of  $\neg \text{gun\_loaded}$  is undercut and so cannot belong to an acceptable argument.

Assuming that  $c$  is absent, the argument,  $\Delta_1$ , consisting of these three “persistence” tuples is in conflict on  $\text{gun\_loaded}$  on 1 with the argument  $\Delta$  above. Each argument disputes the other and in fact neither can form an acceptable argument. If we extend  $\Delta_1$  with the tuple  $\langle p1, 2, F; (\neg \text{fired\_at}(pj, \text{turkey}), 2) \rangle$  then this can now undercut and thus defend against  $\Delta$  using the priority of  $p1$  over  $c1$ . Therefore the extended  $\Delta_1$  is acceptable and the conclusion  $\neg \text{fired\_at}(pj, \text{turkey})$  at 2 is drawn revising the previous conclusions drawn from  $\Delta$ . The process of understanding our story may then proceed by extending  $\Delta_1$ , with  $\langle \text{per}(\text{alive}(\text{turkey}), \cdot), T, F; (\text{alive}(\text{turkey}), T) \rangle$  for  $T = 2, 3, 4$ , resulting in a model that supports  $\text{alive}(\text{turkey})$  at 4. It is based on this inference that we expect readers to respond that the first turkey is alive at 4.

Continuing with the story, after Papa Joe loads the gun and fires again, we can support by forward inferences that the gun fired, that noise was caused, and that the bird stopped chirping, through a chaining of the unit arguments  $c1, c3, c4$ . But  $\text{OBS}(\text{chirp}(\text{bird}), 10)$  supports disputes on all these through the repeated backwards use of the same unit arguments grounded on this observation. We thus have an **exogenous qualification** effect where these conclusions can not be sceptical and so will not be supported by any comprehension model. But if we also consider the stronger (story specific) information in  $p2$ , that this gun does not fire without a noise, together with the backwards inference of  $\neg \text{noise}$  an argument that contains these can undercut the firing of the gun at time 2 and thus defend against disputes that are grounded on  $\text{pull\_trigger}$  at 1 and the gun firing. As a result, we have the effect of blocking the ramification of the causation of  $\text{noise}$  and so  $\neg \text{noise}$  (as well as  $\neg \text{fired\_at}(pj, \text{turkey})$ ) are sceptically concluded. Readers, indeed respond in this way.

With this latter part of the example story we see how our framework addresses the *ramification problem* and its non-trivial interaction with the qualification problem (Thielscher 2001). In fact, a generalized form of this problem is addressed where the ramifications are not chained

only through causal laws but through any of the forms of inference we have in the framework — causal, property or persistence — and through any of the type of inference — forwards or backwards by contradiction.

A comprehension model can be tested, as is often done in psychology, through a series of multiple-choice questions.

**Definition 9.** Let  $M$  be a comprehension model of a story representation  $\mathcal{SR}$ . A possible answer, “ $X$  at  $T$ ”, to a question is **accepted**, respectively **rejected**, iff “ $X$  at  $T$ ” (respectively “ $\neg X$  at  $T$ ”) is supported by  $M$ . Otherwise, we say that the question is **allowed or possible** by  $M$ .

In some cases, we may want to extend the notion of a comprehension model to allow some non-sceptical entailments. This is needed to reflect the situation when a reader cannot find a sceptical answer to a question and chooses between two or more allowed answers. This can be captured by allowing each such answer to be supported by a more general notion of acceptability such as the admissibility criterion of argumentation semantics. For this, we can drop the condition that  $\Delta$  is not undercut by any argument and allow weaker defences, through disputes, to defend back on a dispute that is not at the same time an undercut.

Finally, we note that a comprehension model need not be complete as it does not need to contain all possible sceptical conclusions that can be drawn from the narrative and the entire world knowledge. It is a *subset* of this, given by the subset of the available world knowledge that readers choose to use. This incompleteness of the comprehension model is required for important cognitive economy and coherence properties of comprehension, as trivially a “full model” is contrary to the notion of coherence.

## Computing Comprehension Models

The computational procedure below constructs a comprehension model, by iteratively reading a new part of the story  $\mathcal{SR}$ , retracting existing inferences that are no longer appropriate, and including new inferences that are triggered as a result of the new story part. Each part of the story may include more than one observation, much in the same way that human readers may be asked to read multiple sentences in the story before being asked to answer a question. We shall call each story part of interest a **block**, and shall assume that it is provided as input to the computational procedure.

At a high level the procedure proceeds as in Algorithm 1. The story is read one block at a time. After each block of  $\mathcal{SR}$  is read, a directed acyclic graph  $\mathbb{G}[b]$  is maintained which succinctly encodes all interpretations that are relevant for  $\mathcal{SR}$  up to its  $b$ -th block. Starting from  $\mathbb{G}[b-1]$ , a new tuple is added as a vertex if it is possible to add a directed edge to each  $\langle X, T \rangle$  in the tuple’s condition from either an observation  $\text{OBS}(X, T)$  in the narrative of  $\mathcal{SR}[b]$ , or from a tuple  $\langle \text{arg}(H, B), T^h, d; (X, T) \rangle$  already in  $\mathbb{G}[b]$ . In effect, then, edges correspond to the notion of support from the preceding section, and the graph is the maximal grounded interpretation given the part of the story read.

Once graph  $\mathbb{G}[b]$  is computed, it is used to revise the comprehension model  $\Delta[b-1]$  so that it takes into account the observations in  $\mathcal{SR}[b]$ . The revision proceeds in two steps.

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**Algorithm 1** Computing a Comprehension Model

---

**input:** story  $\mathcal{SR}$ , partitioned in a list of  $k$  blocks, and a set of questions  $Q[b]$  associated with each  $\mathcal{SR}$  block  $b$ .  
Set  $\mathbb{G}[0]$  to be the empty graph.  
**for** every  $b = 1, 2, \dots, k$  **do**  
  Let  $\mathcal{SR}[b]$  be the restriction of  $\mathcal{SR}$  up to its  $b$ -th block.  
  Let  $\mathbb{G}[b] := \text{graph}(\mathbb{G}[b-1], \mathcal{SR}[b])$  be the new graph.  
  Let  $\Pi[b] := \text{retract}(\Delta[b-1], \mathbb{G}[b], \mathcal{SR}[b])$ .  
  Let  $\Delta[b] := \text{elaborate}(\Pi[b], \mathbb{G}[b], \mathcal{SR}[b])$ .  
  Answer  $Q[b]$  with the comprehension model  $\Delta[b]$ .  
**end for**

---

In the first step, the tuples in  $\Delta[b-1]$  are considered in the order in which they were added, and each one is checked to see whether it should remain in the comprehension model. Any tuple in  $\Delta[b-1]$  that is undercut by the tuples in  $\mathbb{G}[b]$ , or disputed and cannot be defended, is retracted, and is not included in the provisional set  $\Pi[b]$ . As a result of a retraction, any tuple  $\langle \arg(H, B), T^h, d; (X, T) \rangle \in \Delta[b-1]$  such that  $\arg(H, B)$  no longer activates  $X$  at  $T$  under  $\Pi[b]$  is also retracted and is not included in  $\Pi[b]$ . This step guarantees that the argument  $\Pi[b]$  is trivially acceptable.

In the second step, the provisional set  $\Pi[b]$ , which is itself a comprehension model (but likely a highly incomplete one), is elaborated with new inferences that follow. The elaboration process proceeds as in Algorithm 2. Since the provisional comprehension model  $\Pi$  effectively includes only unit arguments that are “strong” against the attacks from  $\mathbb{G}$ , it is used to remove (only as part of the local computation of this procedure) any weak arguments from  $\mathbb{G}$  itself (i.e., arguments that are undercut), and any arguments that depend on the former to activate their inferences. This step, then, ensures that all arguments (subsets of  $G$ ) that are defended are no longer part of the revised  $G$ , in effect accommodating the minimality condition for attacking sets. It then considers all arguments that activate their inferences in the provisional comprehension model. The comprehension model is expanded with a new tuple from  $E$  if the tuple is not in conflict with the story nor in direct conflict with the current model  $\Delta$ , and if “attacked” by arguments in  $\mathbb{G}$  then these arguments do not undercut  $\Delta$ , and  $\Delta$  undercuts back. Only arguments coming from the *revised* graph  $\mathbb{G}$  are considered, as per the minimality criterion on considered attacks.

The elaboration process adds only “strong” arguments in the comprehension model, retaining its property as a comprehension model. The discussion above forms the basis for the proof of the following theorem:

**Theorem 1.** Algorithm 1 runs in time that is polynomial in the size of  $\mathcal{SR}$  and the number of time-points of interest, and returns a comprehension model of the story.

*Proof sketch.* Correctness follows from our earlier discussion. Regarding running time: The number of iterations of the top-level algorithm is at most linear in the relevant parameters. In constructing the graph  $\mathbb{G}[b]$ , each pair of ele-

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**Algorithm 2** Elaborating a Comprehension Model

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**input:** provisional comprehension model  $\Pi$ , graph  $\mathbb{G}$ , story  $\mathcal{SR}$ ; all inputs possibly restricted up to some block.  
**repeat**  
  Let  $\mathbb{G} := \text{retract}(\Pi, \mathbb{G}, \mathcal{SR})$ .  
  Let  $E$  include all tuples  $\langle \arg(H, B), T^h, d; (X, T) \rangle$   
  such that  $\arg(H, B)$  activates  $X$  at  $T$  under  $\Pi$ .  
  Let  $\Pi := \Delta$ .  
  Let  $\Pi := \text{expand}(\Delta, E, \mathbb{G})$ .  
**until**  $\Delta = \Pi$   
**output:** elaborated comprehension model  $\Delta$ .

---

ments (unit arguments or observations at some time-point) in  $\mathcal{SR}[b]$  is considered once, for a constant number of operations. The same is the case for the retraction process in the subsequent step of the algorithm. Finally, the loop of the elaboration process repeats at most a linear in the relevant parameters number of times, since at least one new tuple is included in  $\Pi$  in every loop. Within each loop, each step considers each pair of elements (unit arguments or observations at some time-point) in  $\mathcal{SR}[b]$  once, for a constant number of operations. The claim follows. QED

The computational processes presented above have been implemented using Prolog, along with an accompanying high-level language for representing narratives, background knowledge, and multiple-choice questions. Without going into details, the language allows the user to specify a sequence of sessions of the form  $\text{session}(s(B), Qs, Vs)$ , where  $B$  is the next story block to read,  $Qs$  is the set of questions to be answered afterwards, and  $Vs$  is the set of fluents made visible in a comprehension model returned to the user.

The narrative itself is represented by a sequence of statements of the form  $s(B) :: X \text{ at } T$ , where  $B$  is the block in which the statement belongs (with possibly multiple statements belonging in the same block),  $X$  is a fluent or action, and  $T$  is the time-point at which it is observed.

The background knowledge is represented by clauses of the form  $p(N) :: A, B, \dots, C \text{ implies } X$  or  $c(N) :: A, B, \dots, C \text{ causes } X$ , where  $p$  or  $c$  shows a property or causal clause,  $N$  is the name of the rule,  $A, B, \dots, C$  is the rule’s body, and  $X$  is the rule’s head. Negations are represented by prefixing a fluent or action in the body or head with the minus symbol. Variables can be used in the fluents or actions to represent relational rules. Preferences between clauses are represented by statements of the form  $p(N1) >> c(N2)$  with the natural reading.

Questions are represented by clauses of the form  $q(N) ?? (X1 \text{ at } T1, \dots, X2 \text{ at } T2) ; \dots$ , where  $N$  is the name of the question,  $(X1 \text{ at } T1, \dots, X2 \text{ at } T2)$  is the first possible answer as a conjunction of fluents or actions that need to hold at their respective time-points, and  $;$  separates the answers. The question is always the same: “Which of the following choices is the case?”

The implemented system demonstrates real modularity and elaboration tolerance, allowing as input any story nar-

rative or background knowledge in the given syntax, always appropriately qualifying the given information to compute a comprehension model. The system is available at <http://cognition.ouc.ac.cy/narrative/>.

## Evaluation through Empirical Studies

In the first part of the evaluation of our approach we carried a *psychological study* to ascertain the world knowledge that is activated to successfully comprehend example stories such as our example story on the basis of data obtained from human readers. We were interested both in the outcomes of successful comprehension and the world knowledge that contributed to the human comprehension. We developed a set of inferential questions to follow the reading of pre-specified story segments. These assessed the extent to which readers connected, explained, and elaborated key story elements. Readers were instructed to answer each question and to justify their answers using a “think-aloud” method of answering questions while reading in order to reveal the world knowledge that they had used.

The qualitative data from the readers was pooled together and analysed as to the frequencies of the types of responses in conjunction with the information given in justifications and think-aloud protocols. For example, the data indicated that all readers considered Papa Joe to be living on a farm or in a village (q.01, “Where does Papa Joe live?”) and that all readers attributed an intention of Papa Joe to hunt (q.06, “What was Papa Joe doing in the forest?”). An interesting example of variability occurred in the answers for the group of questions 07,08,10,11, asking about the status of the turkeys at various stages in the story. The majority of participants followed a comprehension model which was revised between the first turkey being dead and alive. However, a minority of participants consistently answered that both turkeys were alive. These readers had defeated the causal arguments that supported the inference that the first turkey was dead, perhaps based on an expectation that the desire of the protagonist for turkey would be met with complications. We believe that such expectations can be generated from standard *story knowledge* in the same way as we draw other elaborative inferences from WK.

## Evaluation of the system

Using the empirical data discussed above, we tested our framework’s ability to capture the majority answers and account for their variability. The parts of our example story representation relevant to questions 01 and 06 are as follows:

s(1) :: night at 0.	s(2) :: animal(turkey2) at 2.
s(1) :: xmasEve at 0.	s(2) :: alive(turkey1) at 2.
s(1) :: clean(pj,barn) at 0.	s(2) :: alive(turkey2) at 2.
s(2) :: xmasDay at 1.	s(2) :: chirp(bird) at 2.
s(2) :: gun(pjGun) at 1.	s(2) :: nearby(bird) at 2.
s(2) :: longWalk(pj) at 1.	s(2) :: aim(pjGun,turkey1) at 2.
s(2) :: animal(turkey1) at 2.	s(2) :: pulltrigger(pjGun) at 2.

The two questions are answered after reading, respectively, the first and second blocks of the story above:

session(s(1),[q(01)],\_). session(s(2),[q(06)],\_).

with their corresponding multiple-choice answers being:

```
q(01) ??
lives(pj,city) at 0;    lives(pj,hotel) at 0;
lives(pj,farm) at 0;   lives(pj,village) at 0.

q(06) ??
motive(in(pj,forest),practiceShoot) at 3;
motive(in(pj,forest),huntFor(food)) at 3;
(motive(in(pj,forest),catch(turkey1)) at 3,
 motive(in(pj,forest),catch(turkey2)) at 3);
motive(in(pj,forest),hearBirdsChirp) at 3.
```

To answer the first question, the system uses the following background knowledge:

```
p(11) :: has(home(pj),barn) implies lives(pj,countrySide).
p(12) :: true implies -lives(pj,hotel).
p(13) :: true implies lives(pj,city).
p(14) :: has(home(pj),barn) implies -lives(pj,city).
p(15) :: clean(pj,barn) implies at(pj,barn).
p(16) :: at(pj,home), at(pj,barn) implies has(home(pj),barn).
p(17) :: xmasEve, night implies at(pj,home).
p(18) :: working(pj) implies -at(pj,home).
p(111) :: lives(pj,countrySide) implies lives(pj,village).
p(112) :: lives(pj,countrySide) implies lives(pj,farm).
p(113) :: lives(pj,village) implies -lives(pj,farm).
p(114) :: lives(pj,farm) implies -lives(pj,village).
p(14) >> p(13).    p(18) >> p(17).
```

By the story information, p(17) implies at(pj,home), without being attacked by p(18), since nothing is said in the story about Papa Joe working. Also by the story information, p(15) implies at(pj,barn). Combining the inferences from above, p(16) implies has(home(pj),barn), and p(11) implies lives(pj,countrySide). p(12) immediately dismisses the case of living in a hotel (as people usually do not), whereas p(14) overrides p(13) and dismisses the case of living in the city. Yet, the background knowledge cannot unambiguously derive one of the remaining two answers. In fact, p(111), p(112), p(113), p(114) give arguments for either of the two choices. This is in line with the variability in the empirical data in terms of human answers to the first question.

To answer the second question, the system uses the following background knowledge:

```
p(21) :: want(pj,foodFor(dinner)) implies
motive(in(pj,forest),huntFor(food)).
p(22) :: hunter(pj) implies
motive(in(pj,forest),huntFor(food)).
p(23) :: firedat(pjGun,X), animal(X) implies
-motive(in(pj,forest),catch(X)).
p(24) :: firedat(pjGun,X), animal(X) implies
-motive(in(pj,forest),hearBirdsChirp).
p(25) :: xmasDay implies
want(pj,foodFor(dinner)).
p(26) :: longWalk(pj) implies
-motive(in(pj,forest),practiceShooting).
p(27) :: xmasDay implies
-motive(in(pj,forest),practiceShooting).
```

By the story information and parts of the background knowledge not shown above, we can derive that Papa Joe is a hunter, and that he has fired at a turkey. From the first inference, p(22) already implies that the motivation is to hunt for food. The same inference can be derived by p(25) and p(21), although for a different reason. At the same time, p(23) and



p(24) dismiss the possibility of the motivation being to catch the two turkeys or to hear birds chirp, whereas story information along with either p(26) or p(27) dismiss also the possibility of the motivation being to practice shooting.

The background knowledge above follows evidence from the participant responses in our psychological study that the motives in the answers of the second question can be “derived” from higher-level desires or goals of the actor. Such high-level desires and intentions are examples of *generalizations* that contribute to the coherence of comprehension, and to the creation of *expectations* in readers about the course of action that the story might follow in relation to fulfilling desires and achieving intentions of the protagonists.

## Related Work

Automated story understanding has been an ongoing field of AI research for the last forty years, starting with the planning and goal-oriented approaches of Schank, Abelson, Dyer and others (Schank and Abelson 1977; Dyer 1983); for a good overview see (Mueller 2002) and the website (Mueller 2013). Logic-related approaches have largely been concerned with the development of appropriate representations, translations or annotations of narratives, with the implicit or explicit assumption that standard deduction or logical reasoning techniques can subsequently be applied to these. For example, the work of Mueller (Mueller 2003), which in terms of story representation is most closely related to our approach, equates various modes of story understanding with the solving of satisfiability problems. (Niehaus and Young 2009) models understanding as partial order planning, and is also of interest here because of a methodology that includes a controlled comparison with human readers.

To our knowledge there has been very little work relating story comprehension with computational argumentation, an exception being (Bex and Verheij 2013), in which a case is made for combining narrative and argumentation techniques in the context of legal reasoning, and with which our argumentation framework shares important similarities. Argumentation for reasoning about actions and change, on which our formal framework builds, has been studied in (Vo and Foo 2005; Michael and Kakas 2009).

Many other authors have emphasized the importance of commonsense knowledge and reasoning in story comprehension (Silva and Montgomery 1977; Dahlgren, McDowell, and Stabler 1989; Riloff 1999; Mueller 2004; Mueller 2009; Verheij 2009; Elson and McKeown 2009; Michael 2010), and indeed how it can offer a basis for story comprehension tasks beyond question answering (Michael 2013b).

## Conclusions and Future Work

We have set up a conceptual framework for story comprehension by fusing together knowhow from the psychology of text comprehension with established AI techniques and theory in the areas of Reasoning about Actions and Change and Argumentation. We have developed a proof of concept automated system to evaluate the applicability of our frame-

work through a similar empirical process of evaluating human readers. We are currently, carrying out psychological experiments with other stories to harness world knowledge and test our system against the human readers.

There are still several problems that we need to address to complete a fully automated approach to SC, over and above the problem of extracting through Natural Language Processing techniques the narrative from the free format text. Two major such problems for our immediate future work are (a) to address further the computational aspects of the challenges of cognitive economy and coherence and (b) the systematic extraction or acquisition of common sense world knowledge. For the first of these we will investigate how this can be addressed by applying “computational heuristics” on top of (and without the need to reexamine) the solid semantic framework that we have developed thus far, drawing again from psychology to formulate such heuristics. In particular, we expect that the psychological studies will guide us in modularly introducing computational operators such as *selection*, *dropping* and *generalization operators* so that we can improve the coherence of the computed models.

For the problem of the systematic acquisition of world knowledge we aim to source this (semi)-automatically from the Web. For this we could build on lexical databases such as WordNet (Miller 1995), FrameNet (Baker, Fillmore, and Lowe 1998), and PropBank (Palmer, Gildea, and Kingsbury 2005), exploring the possibility of populating the world knowledge theories using archives for common sense knowledge (e.g., Cyc (Lenat 1995)) or through the automated extraction of commonsense knowledge from text using natural language processing (Michael and Valiant 2008), and appealing to textual entailment for the semantics of the extracted knowledge (Michael 2009; Michael 2013a).

We envisage that the strong inter-disciplinary nature of our work can provide a concrete and important test bed for evaluating the development of NMR frameworks in AI while at the same time offering valuable feedback for Psychology.

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